Research on Risk Identification of Human Errors of Train Dispatchers in High-speed Railway

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Abstract. In order to prevent and reduce the human error of high-speed railway train dispatchers, the method of TOmada de Decisão Interativa Multicritério (TODIM) and Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE-II) was used to identify the human error risk of train dispatchers. In this paper, the risk attribute set is constructed from the three dimensions of human error probability, human error severity, and human error detection degree. Considering the fuzziness and uncertainty of risk attributes, it is represented by 2-tuples. At the same time, the entropy weight method is used to calculate the attribute weight. In order to reduce the defects of using TODIM and PROMETHEE-II methods alone, the two methods are integrated and a new risk identification model is constructed. And the model is applied to the risk identification of human errors in dispatching command operations. The results show that the model can effectively identify the human error risk of train dispatchers, and the top three human error modes are the inversion of the operating procedure, the wrong handling decision and the issuance of invalid orders.

Keywords- train dispatchers; human error; TODIM; PROMETHEE-II; entropy weight method; risk identification

1. Introduction

As the nerve centre of the railway transportation system, the high-speed railway train dispatching system is an important barrier for the safe, efficient and punctual operation of high-speed trains[1]. Its reliability is directly related to the safety of the entire high-speed railway transportation system. With the continuous advancement of science and technology, the reliability of system hardware is getting higher and higher, and the reliability of human factors has become the bottleneck restricting the reliability of the system. How to identify the human error risk points of train dispatchers and determine the priority of risk control has become the primary goal of human error research. Therefore, researching and establishing a human error risk identification model is of great significance for improving the safety management level of high-speed railways and reducing the human error of train dispatchers.

The high-speed railway train dispatching system is a typical man-machine system[2]. The train dispatcher has direct control over the on-site traffic, and the train dispatcher uses various equipment to transmit information and issue dispatching orders, so as to ensure the safe and punctual operation of the train. Once an operation error occurs, it is easy to induce a major driving accident and bring great harm to the life and property of passengers. Although human error brings huge risks and hazards, the current risk identification for human error of train dispatchers mainly relies on the risk matrix method. Although the risk matrix method is simple, the calculation is rough and the accuracy is not high. Aiming at the human factor reliability and human error within the railway system. Li et al.[3] using Decision-making Trial and Evaluation Laboratory and Interpretation Structure Modelling to conduct an in-depth analysis of factors affecting human errors of railway maintenance personnel. Wang et al.[4] constructed a structured human error behavior recognition method to identify the risk of human error in the subway traffic dispatching system. Wu et al.[5] constructed a risk evaluation index system from four aspects: human error probability, human error detection, human error importance, and accident severity. Using intuitionistic triangular fuzzy numbers and Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) analyzed the high-speed rail dispatcher's people were sorted by mistake. It can be seen that the research on human error in the railway system mainly focuses on the analysis of the influencing factors of human error, and rarely conducts risk identification for the human error of train dispatchers. In other respects, Ebrahimnejad et al.[6] believed that both risk identification and risk assessment are essentially a multi-attribute decision-making problem. Therefore, many multi-attribute decision-making models have been applied to the field of risk identification. Considering the ambiguity of risk indicators or risk attributes in the evaluation process, fuzzy set theory and multi-attribute decision-making methods have become popular research objects in the field of risk identification[7],[8],[9],[10].

The above research methods have certain reference significance for the risk identification of human errors in high-speed railway train dispatchers. Compared with fuzzy sets, 2-tuples has less information loss in the process of aggregation, and has better reliability and accuracy, so it can be used to characterize risk attributes[11]. TODIM is a classic multi-attribute decision-making method, but there are two disadvantages in the use of TODIM, one is only applicable to the case where the data is a real number, and the other is the compensation problem[12],[13]. Therefore, this paper uses PROMETHEE-II to improve TODIM and proposes an integrated TODIM-PROMETHEE model. The risk attribute set is constructed from the three aspects of human error probability, human error detection degree and human error severity, and use 2-tuples as the attribute evaluation language to identify the risk of human error for high-speed railway train dispatchers. In order to provide ideas and suggestions for high-speed railway traffic safety management.

2. 2-tuples linguistic

2-tuples is a method of linguistic evaluation information based on symbol translation. Because of its simple and efficient calculation, accurate and reliable results, it is often used to describe some indicators of ambiguity, uncertainty and subjectivity[14]. Its basic definitions are as follows.

Definition 1: Let $S=(s_i|i=1, 2, \dots, g)$ be a linguistic term set with odd cardinality, and $\beta(\beta\in[0, g])$ be the result of a symbolic aggregation operation. $i = \text{round}(\beta)$, ("round" is the common rounding operation), $\alpha = \beta - i$, make $i\in[0, g]$, $\alpha\in[-0.5, 0.5)$, and α is the symbolic translation value s_i.

Definition 2: Let $S=(s_i|i=1, 2, \dots, g)$ be a linguistic term set with odd cardinality, $\beta\in[0, g]$ be a value representing the result of a symbolic aggregation operation, then the 2-tuples of β can be obtained through the function Δ:

$$\Delta:[0,g]\rightarrow S\times[-0.5,0.5)$$
$$\Delta(\beta)=(s_i,\alpha)=\begin{cases} s_i & i=round(\beta) \\ \alpha & \alpha=\beta-i \end{cases} \tag{1}$$

Definition 3: Let $S=(s_i|i=1, 2, \dots, g)$ be a linguistic term set with odd cardinality, and (s_i, α) be a 2-tuple. There exists a function Δ^{-1} to convert a 2-tuple into its equivalent numerical value$\beta\in[0, g]$ where:

$$\Delta^{-1}: S \times [-0.5, 0.5) \to [0,1]$$
$$\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta \tag{2}$$

Definition 4: Assume that $S_k = (s_k, \alpha_k)$, $S_l = (s_l, \alpha_l)$ are two 2-tuples on the 2-tuple linguistic sets $S=\{(s_i, \alpha_i)|i=1, 2, \ldots, g\}$, Then the size comparison rules of S_k and S_k are as follows::

If $k > l$, then $S_k \succ S_l$。

If $k = l$, when $\alpha_k > \alpha_l$, then $S_k \succ S_l$; when$\alpha_k = \alpha_l$, then $S_k \sim S_l$; when $\alpha_k < \alpha_l$, then $S_k \prec S_l$.

Definition 5: Let $S=\{(s_i, \alpha_i)|i=1, 2, \ldots, g\}$ is the 2-tuple linguistic sets, then its arithmetic weighted average operator WA(S) is defined asfollows.

$$\mathrm{WA}(S) = \Delta\left(\sum_{i=1}^{g} \Delta^{-1}(s_i, \alpha_i) w_i\right) \tag{3}$$

where $\boldsymbol{w}=(w_i|i=1, 2, \ldots, g)$ is the weight vector of S, with $w_i \in [0, 1]$, $\sum_{i=1}^{g} w_i = 1$.

Definition 6: Assume that $S_k = (s_k, \alpha_k)$, $S_l = (s_l, \alpha_l)$ are two 2-tuples on the 2-tuple linguistic sets $S=\{(s_i, \alpha_i)|i=1, 2, \ldots, g\}$, then we can get the Hamming distance:

$$d(S_k, S_l) = \frac{1}{g}\left|\Delta^{-1}(S_k) - \Delta^{-1}(S_l)\right| \tag{4}$$

3. Risk identification model based on TODIM-PROMETHEE-II

3.1. Human error risk attribute set

The risk matrix method is a commonly used method in risk identification. It takes the probability of risk occurrence and the severity of risk occurrence as row elements and column elements respectively, and sorts risks according to the product of the two. In reality, high-speed railway dispatching tasks are generally completed jointly by the principal train dispatcher and assistant train dispatcher. In order to ensure safety, the principal dispatcher and assistant dispatcher will conduct self-check and mutual check during the completion of tasks, and human error detection will occur. At the same time, referring to the ideas of the 3 risk attributes of occurrence, severity, and detection in Failure Mode and Effects Analysis, (FMEA), the risk attributes of human errors are divided into 3 types. R_1 is the frequency of human errors; the severity of human errors R_2 is the severity of the consequences of human errors; the degree of detection of human errors R_3 is the degree of difficulty in detecting human errors.

Due to the ambiguity and uncertainty in the description of risk attributes. Here, 2-tuples is used to characterize the above 3 risk attributes, as shown in Table 1.

Table 1. Linguistic level terms of risk modes.

R_1	R_2	R_3	2-tuples
very low	very mild	very easy	s_0
low	mild	easy	s_1
lower	milder	easier	s_3
medium	medium	medium	s_4
higher	serious	difficult	s_5
higher	more serious	More difficult	s_6
Very high	Very serious	Very difficult	s_3

3.2. Human error risk identification description

Suppose $A=(A_i|i=1, 2, \ldots, m)$ is a set of human error modes for the high-speed train dispatchers, $R=(R_j|j=1, 2, \ldots, n)$ is the set of human error risk attributes, and $\boldsymbol{w}=(w_j|j=1, 2, \ldots, n)$ is the weight vector of risk attributes, where $w_i \in [0, 1]$, and $\sum_{i=1}^{g} w_i = 1$. The 2-tuples evaluation matrix of R_j of human error mode A_i about risk attributes is $\boldsymbol{P} = \left(p_{ij}\right)_{m \times n}$.

3.3. Obtain attribute weight with entropy weight method

For the risk attribute R_j, the weighted Hamming distance of human error modes A_i and A_t is:

$$D_{ij}(w) = \sum_{t=1}^{m} d\left(A_{ij}, A_{tj}\right) \tag{5}$$

Then the total deviation between human error mode A_i and other human error modes is:

$$D_j(w) = \sum_{i=1}^{m} D_{ij}(w) \tag{6}$$

Then the entropy value of risk attribute R_j is:

$$E_j = -\sum_{i=1}^{m} \frac{D_{ij}(w)}{D_j(w)} \ln \frac{D_{ij}(w)}{D_j(w)} \tag{7}$$

The closer the $\frac{D_{ij}(w)}{D_j(w)}$ (j=1, 2, …, n) value is, the larger the entropy value E_j is, indicating that the smaller the deviation between all attributes, the smaller the differentiation of attributes, and the smaller the weight of this attribute. In order to avoid excessive pursuit of maximum deviation, a nonlinear programming model is established according to the goal of minimum product of attribute weight value and attribute entropy value:

$$Min \sum_{j=1}^{m} w'_j E_j$$
$$st. \begin{cases} \sum_{j=1}^{m} \sqrt{w'_j} = 1 \\ w'_j > 0 \end{cases} \tag{8}$$

Construct the Lagrangian auxiliary function and get the solution：

$$w'_j = \left(E_j \left(\sum_{j=1}^{n} \frac{1}{E_j} \right) \right)^{-2} \tag{9}$$

After normalization, attribute weight is obtained:

$$w_j = \frac{w'_j}{\sum_{j=1}^{n} w'_j} \tag{10}$$

3.4. Risk identification procedure

As a classic multi-attribute decision-making method, TDOIM's most prominent feature is that it considers the psychological behavior of the decision-maker when evaluating, while most other methods assume that the decision-maker is completely rational.

However, TDOIM has two obvious disadvantages, one is that it can only process real number, and the other is the impact of compensation problem, that is, the deficiency of some attributes may be offset by the excellent performance of other attributes, resulting in errors or extremely opposite ranking order. For the first disadvantage, it can be solved by comparison rules and distances of 2-tuples. For the second disadvantage, POMETHEE-II is refined using population advantages and population disadvantages, which calculate inflows and outflows in order to increase confidence in risk identification.

Step1: Evaluate the human error pattern Ai with respect to the risk attribute Rj with binary semantics, and get the matrix $\boldsymbol{P}=\left(p_{ij}\right)_{m\times n}$.

Step2: Use Equation (5) to Equation (10) to calculate risk attribute weight w_j

Step3: Calculate the dominance matrix $\boldsymbol{\Phi}_j=\left[\phi_j\left(A_i,A_t\right)\right]_{m\times m}$ of human error mode A_i relative to A_t under attribute R_j.

$$\phi_j\left(A_i,A_t\right)=\begin{cases}\sqrt{\dfrac{w_j d\left(p_{ij},p_{tj}\right)}{\sum_{j=1}^{n} w_j}} & p_{ij}\succ p_{tj}\\ 0 & p_{ij}\sim p_{tj}\\ -\dfrac{1}{\theta}\sqrt{\dfrac{\sum_{j=1}^{n} w_j d\left(p_{ij},p_{tj}\right)}{w_j}} & p_{ij}\prec p_{tj}\end{cases} \tag{11}$$

Where, $d\left(p_{ij},p_{tj}\right)$ is the Hamming distance between p_{ij} and p_{tj}. The parameter $\theta(\theta>0)$ is the loss attenuation coefficient, its value is adjusted appropriately according to the preference of the decision maker. If $\theta<1$, it means that the decision maker is more sensitive to loss and has a greater degree of loss aversion; if $\theta=1$, it means that the decision maker is completely rational; if $\theta>1$, it means that the decision maker is not sensitive to loss.

Step4: Calculate the overall dominance under all attributes.

$$\phi\left(A_i,A_t\right)=\sum_{j=1}^{n} w_j\phi_j\left(A_i,A_t\right) \tag{12}$$

Step5: Obtain outflow $\phi^{+}\left(A_i\right)$, inflow $\phi^{-}\left(A_i\right)$, and net flow $\phi\left(A_i\right)$.

$$\phi^{+}\left(A_i\right)=\sum_{t=1}^{m}\phi\left(A_i,A_t\right) \tag{13}$$

$$\phi^{-}\left(A_i\right)=\sum_{t=1}^{m}\phi\left(A_t,A_i\right) \tag{14}$$

$$\phi\left(A_i\right)=\phi^{+}\left(A_i\right)-\phi^{-}\left(A_i\right) \tag{15}$$

Step6: Sort according to the net flow $\phi\left(A_i\right)$, the larger the value of $\phi\left(A_i\right)$, the higher the risk ranking of the human error mode A_i.

4. An Illustrative Example

4.1. Human error risk ranking

Dispatching command is an important means for train dispatcher to command train operation, organize construction and maintenance, and deal with emergencies. Considering the complex daily operation of train dispatchers in high-speed railway and the importance of dispatching command, we use dispatching command to identify human error risks. Select 6 typical human error modes in dispatching command operations for analysis, and the 6 error modes are shown in Table 2.

Table 2 Human error models

Number	Human error model
A_1	Disposal decisions were wrong, and before the dispatch order was issued, the site situation was not fully understood and the opinions of relevant personnel were not listened to. If the turnout loses the condition that it can use the guiding signal to pick up

	the car, issue an order to pick up the car with the guiding hand signal, resulting in disagreement with the on-site personnel.
A_2	The command was issued at the wrong timing. The main manifestations are that the timing of the construction maintenance order is later than the time specified in the order content, and the speed limit order is issued under the condition that the number of ordered units is not satisfied.
A_3	The dispatch command content is inaccurate. The content of the issued order is inconsistent with the specific construction registration content, and more words, less words, and wrong words are common.
A_4	The location of the dispatch command is incomplete. Commands related to train operation were not given to station attendants, orders involving sections were not given to station attendants at both ends, orders related to the operation of train locomotives were not given to drivers, and orders related to marshalling content and train supervisory responsibilities were not given to operating conductors, etc.
A_5	The work procedure is reversed. It is mainly manifested in issuing a power outage order first, and then issuing a quasi-power outage, or issuing a power outage order in advance if the operation area does not meet the power outage conditions.
A_6	Issue an invalid command. Including the use of verbal instructions instead of dispatching orders, such as issuing an order for passenger car wireless telephone failure, which is not issued to the final station of the train at one time, and cannot accept orders in other sections when the train is scheduled to pass through other sections .

By consulting the relevant data of the railway bureau and expert evaluation, the 2-tuples risk assessment information of 6 typical human errors is obtained, as shown in Table 3.

Table 3 2-tuple linguistic risk assessment information

Number	R_1	R_2	R_3
A_1	$(s_4, 0)$	$(s_5, 0.2)$	$(s_4, -02)$
A_2	$(s_4, 0.2)$	$(s_3, 0)$	$(s_3, 0)$
A_3	$(s_5, 0.3)$	$(s_4, 0.1)$	$(s_4, 0.3)$
A_4	$(s_4,-0.3)$	$(s_4, 0)$	$(s_3,-0.2)$
A_5	$(s_3, 0.3)$	$(s_5, 0.3)$	$(s_3, 0)$
A_6	$(s_3, 0)$	$(s_3, -0.2)$	$(s_1, 0.2)$

Firstly, use Equation (5)~ Equation (10) to calculate the weights of the 3 risk attributes as w_1=0.402, w_1=0.257, and w_1=0.341. Then calculate the outflow $\phi^+(A_i)$, inflow $\phi^-(A_i)$ and net flow $\phi(A_i)$ according to Equation (11)~ Equation (15). Since the high-speed railway dispatching system is a safety-critical system, the value of θ in Equation (11) is 0.5. Finally, risk ranking was conducted according to and net flow value $\phi(A_i)$, and the ranking results were shown in Table 4.

Table 4 Risk ranking results

Number	$\phi^+(A_i)$	$\phi^-(A_i)$	$\phi(A_i)$	Rank
A_1	-0.0342	-0.5079	0.4737	2
A_2	-1.2101	0.0598	-1.2699	6
A_3	-0.8231	-0.0282	-0.7949	5
A_4	-0.1256	-0.3857	0.2601	4
A_5	0.0493	-0.8339	0.8832	1
A_6	-0.0705	-0.4410	0.3705	3

The ranking results were compared with the experience evaluation results of on-site safety supervisors, and the results were basically consistent, which also verified the applicability of the risk identification model from the side.

From the ranking, it can be seen that the three human error modes of " The work procedure is reversed (A_5)", " disposal decisions were wrong (A_1)" and "issue of invalid command (A_6)" are in the top 3. It should arouse the attention of train dispatchers and safety managers.

4.2. Comparative analysis

In order to further verify the effectiveness of the model in this paper, the ranking results of the human error risk model of the dispatch order in the case were compared with the results calculated by TODIM in paper [12] and PROMETHEE-II in paper[15], as shown in Table 5.

Table 5 Risk ranking results comparison

Ranking method	A_1	A_2	A_3	A_4	A_5	A_6
TODIM-PROMETHEE-II	2	6	5	4	1	3
TODIM	2	4	5	6	1	3
PROMETHEE-II	2	6	4	5	1	3

The top 3 rankings of the 3 methods are A_5, A_1 and A_6, indicating that the 3 methods have basically the same effect in identifying the riskiest human error mode. However, the ranking results of A_2, A_3 and A_4 are different, because compared with the TODIM method in paper [12], the method in this paper reduces the defects caused by the attribute compensation problem of the TODIM method. Compared with the PROMETHEE-II method in paper [15], the method in this paper effectively reflects the psychological behavior of decision makers, making the calculation results more objective. This further verifies the superiority of the method in this paper.

5. Conclusion

(1) The risk attribute set is constructed from the three dimensions of human error probability, human error severity, and human error detection degree, and the attributes are represented by binary semantics, which provides ideas for the construction and evaluation of human error risk attributes.

(2) A set of risk attributes is constructed from three dimensions: probability of human error, severity of human error, and detection degree of human error. The attributes are characterized by binary semantics, which provides ideas for the construction and evaluation of human error risk attributes.

(3) The entropy weight method is used to calculate the weight of the risk attribute, which improves the calculation accuracy of the attribute weight. A new model was proposed by integrating TODIM and POMETHEE-II, which overcomes the shortcomings of the two methods used alone.

(4) Safety has always been the primary goal of railway transportation management. Risk identification is an important means of railway safety management. Although the new model provides a new way of thinking in risk identification, it still has certain limitations. For example, the assessment of risk attributes is largely Relying on the subjective experience of domain experts, how to eliminate the subjectivity of expert evaluation is still the direction of future efforts.

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